Big Data's Impact on Jordan Banks' Organizational Innovation: Examining the Moderating Effects of Management Commitment and Mediating Knowledge Sharing

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ABSTRACT

This research comprehensively examines the impact of big data integration on organizational innovation in the context of Jordanian banks. It builds on prior research to explore the role of "Big Data's volume, velocity, variety and veracity." Organizational Innovation and Leadership Besides managerial commitment and knowledge sharing, organizational innovation and leadership are also crucial. The constructs have a proven validity and reliability for at least preliminary validation analysis. A major result of big data is a significant effect of volume, velocity and variety on organizational innovations. Further, in reinforcing the need for knowledge sharing as an important mediator of decision-making and problem solving, the study also emphasises the importance of management's support to facilitate this means of communication process with innovative outcomes within a particular organization. The paper suggests for better insight of the importance of data analysis in institutional innovation to cope with external environmental concerns.

Keywords: Big Data, Jordan Banks, Management Commitment, Organizational Innovation, Shared Knowledge
JEL Classifications: O31, G21, M15

1. INTRODUCTION

Businesses are spending more on big data and analytics to stay ahead of their competition, and acquire better business insights (Tunc-Abubakar et al., 2023). big data is an increasingly used in today's rapid business world: And the banking sector is one of these business (Cerra et al., 2012). Still, we need to understand more about knowing how theyconnected between them for impact on innovation outputs that flow from the adoption and implementation of bigdata by banks (Al-Dmour et al., 2023), Nowadays, using Big Data technology had been revolutionary tool T to help Jordanian banks during their journy trends in competitive market structure and generate new sources innovation within markets (Van Rijmenam et al., 2019).

Businesses have started embracing big data, which has been dubbed the new oil for today's digital economy since it contains so much valuable information (Sivarajah et al., 2013), Big data is characterized by its truth, diversity, velocity, and volume (Ohlhorst, 2012), is quickly becoming a vital organizational resource that might aid companies in producing business insights (Ghasemaghaei and Calic, 2019; Wamba et al., 2017), Big data insights might be crucial for companies looking to innovate. However, many companies find it challenging to leverage big data to improve outcomes like innovation competency (Johnson et al., 2017). Others question whether vast amounts of varied data collected from several sources can yield insightful information (LaValle et al., 2010). In actuality, 48% of businesses invested in big data in 2016—a 3% increase over 2015 (Van der Meulen et al., 2016).

Current research is based on personal experience, and little is known about big data's role in producing data-driven insights.

Additionally, a key component of giving organizations a competitive edge is increasing organizational innovation potential (Tan et al., 2015).

Today's banks are driven to look for state-of-the-art technology solutions because they prioritize quick data processing better customer service and efficient risk management the usage of big data is a notable technological achievement (Nguyen, 2020), This has changed how banks operate, and how decisions are made, and how they approach innovation, Big Data, which is characterised by its volume, velocity, and diversity, includes large and complex datasets that are difficult for standard data processing to handle effectively (Dicuonzo et al., 2019).

Big Data has an immediate effect on banks' ability to innovate. Big Data may be used to improve the efficiency of banking operations, provide innovative products and services, and optimise internal procedures (Rialti et al., 2018) Implementing big data presents difficulties, in the present era of Big Data, Knowledge Management, and Innovation integration, policies will prioritize socially inclusive economic development and sustainability, this phenomena is interdisciplinary and will be driven by the increasing usage of artificial intelligence (AI) and smart machine technologies (Ordóñez de Pablos and Lytras, 2018), effective use of knowledge is crucial for organizations, as information is a valuable resource that should not be wasted. Instead, knowledge should be actively handled. Organizational knowledge can be managed through many techniques technology has made it easier to collect and store information (Train and Egbu, 2006), A high level of managerial dedication has a beneficial impact on company earnings and competitiveness, also discovered that organizing work teams has a favourable impact on competitive benefits and, as a result, economic benefits (Oropesa-Vento et al., 2015).

2. GOAL OF STUDY

This study aims to clarify the connection between organizational innovation and big data use in Jordanian banks, how shared knowledge sharing mediates this relationship, and the moderating effect of managerial commitment. The primary goal is to assess the extent to which Jordanian banks are now utilising big data.

- Analyzing how Jordanian banks' use of big data affects innovation
- Explain how the link between "organisational innovation" and "Big Data" utilization is mediated by knowledge sharing
- Finding knowledge of how administrative dedication may improve the connection between organizational innovation and knowledge sharing.

3. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The technology acceptance model offers an approach for assessing how people perceive and engage with new technologies in data processing and deployment (Marangunić and Granić 2013), the utilization of big data in businesses has grown significantly throughout the last 10 years, As scientists started to understand

the connection between large data usage, which is based on organizational learning theory, is that businesses use knowledge from big data sets to enhance corporate social performance (CSP), big data's impact on innovation performance has drawn a lot of attention studies the relationship between innovation efficacy and efficiency in banks and the three main attributes of big data volume, diversity, and velocity, the results show that data velocity outperforms other big data characteristics in terms of improving innovation performance (Calic and Ghasemaghaei, 2021), compared big data attributes, data velocity is found to be more significant in enhancing company innovation performance (Ghasemaghaei and Calic, 2020), the basis for this is provided by the resource-based and dynamic capability perspectives, the effect of big data analytics on the creative activities of MSMEs.

Our study advances the field's understanding of big data analytics and innovation while providing MSMEs with practical guidance on leveraging big data analytics to support entrepreneurial innovation (Zheng et al., 2022). by offering fresh approaches to data information and producing fresh choices for businesses' innovation process, we find encouraging evidence that big data analytics is a significant factor in determining the market acceptance of product innovations as well as a company's likelihood of becoming a product innovator when we use German company-level information inside a conceptual manufacturing framework (Niebel et al., 2019).

Huge data in partnerships and market leadership in innovation, to keep ahead of the competition and to increase activity, businesses are inventing and utilizing big data to produce new products and services and to take advantage of marketing opportunities, this framework for analyzing the impact of big data is provided, huge data is both collected and used by organizations; it is partially produced by the number of online business and customer transactions. Big data, its analytics, and its applications can be interpreted as markers of an organization's capacity for innovation in response to market opportunities (Wright et al., 2019), adding to this, the theory of dynamic capability offers additional information about how data availability (DA) and huge data analytics capabilities (BDAC) might improve innovation capabilities (IC), a firm's capacity for innovation is greatly enhanced by high (BDAC) levels that are backed by a wealth of data that is readily available (Ramadan et al., 2020), Even if the corpus of existing work provides a basis for comprehending the influence of huge data on innovation, further research is necessary to completely understand the complex relationships between big data attributes and organizational innovation. Consequently, the subsequent hypotheses are put forth.

- H_1: Big data is positively correlated with Organizational innovation.

3.1. Knowledge Sharing Plays a Role in Mediating

Developing a competitive advantage requires both knowledge management and big data, and their functions are intertwined (Alavi and Leidner, 1999; Nonaka, 1994), Despite their significance, the connection between big data and knowledge management has not received much attention (Davenport, 2013; LaValle et al., 2010; O'Leary, 2014), the main objective of big

data and knowledge management is to provide businesses with a competitive advantage (Chen et al., 2012; George et al., 2014; Grant, 1996) effective information sharing is made possible by big data text analytics, which is essential for monitoring and organizing external knowledge sources giving businesses a competitive edge is the main objective of knowledge management and big data effective information interchange is made possible by big data text analytics, which is essential for monitoring and classifying external knowledge sources (Chen et al., 2012 and Davenport, 2013).

Additionally, Birkinshaw and Morrison (1995) looked into the connection between innovation and organizational structures, according to their research companies that have organizational structures that make it easier for people to integrate tasks and share resources are often more innovative than companies that don't have these kinds of collaborative processes, to optimize its efficacy, data and information management needs to be balanced and under control. Large-scale dataset management presents a big problem for organizations that want to share and integrate important data across several platforms and maintain alignment with business partners (Hsseinoiun, 2018).

According to the knowledge-based theory, controlling knowledge-based resources rather than tangible resources will help businesses achieve longer-term higher performance and competency (Ater, 2023). To help with decision-making and planning regarding who should do what during the strategy implementation process, information should be exchanged and further information should be retrieved from the institution's memory (Lunenburg, 2012), Information communication is a crucial method for creating and gaining knowledge at work and It serves as the cornerstone of knowledge management and information exchange is crucial to knowledge management systems' effectiveness (Wang and Noe, 2010).

Consequently, it implies that knowledge acts as an organization's competitive advantage when applied to regular organizational tasks, studies show that information sharing improves team performance overall, lowers production costs, and expedites the completion of new product development projects (Mesmer-Magnus and DeChurch, 2009; Tsai, 2001; Wang and Noe, 2010).

Analyzing factors like the type of knowledge (explicit vs. tacit, for example) might reveal which kinds of knowledge are most important for the advancement of different businesses (Polanyi, 1967), companies can determine when and where big data contributions can be most beneficial by using this technique (Bhimani and Willcocks, 2014). Furthermore, according to Alavi and Leidner (2001), these variables offer businesses information regarding the preservation of intangible assets by assisting them in determining whether their data is susceptible to competitive hazards and whether precautions should be taken to secure it.

Knowledge sharing is considered as the track that needs development to enhance the performance and innovation of organizations in many studies (Cummings, 2003; Gurteen, 1999), In this respect it becomes crucial to find out how knowledge-sharing process affects inventive power and competence of firms operating

in Kahramanmaras which was definition aim of study, also studied how innovative capabilities have an impact on companies' innovation performance. It would add to the furthering of knowledge about how the process of sharing knowledge could have potentially damaging effects on innovation, and as such, strengthen the organizational innovation milieu given its performance and capacity. By investigating 78,000-firm–year observations on innovation activities and performance and capacity investments we utilise to advance our understanding of innovation shows that the relationship between capacity investment and innovation is more complex than this – more knowledge does not necessarily lead to better outcomes: knowledge transfer seems beneficial while generations prior have noted that KBAM.

- H_2: Knowledge sharing acts as a mediator in the correlation between organizational innovation and big data
- H_3: Big data is positively correlated with Shared knowledge
- H_4: Knowledge sharing is positively correlated with organizational innovation.

3.2. Moderating Influence of Management Commitment

To allocate resources, develop talents, and provide businesses with a competitive edge, top management commitment is crucial (Chadwick et al., 2015; Sirmon et al., 2007). Because authority, duties, norms, and procedures are clearly defined, this strong organizational commitment creates an atmosphere that is favourable for process innovation (Tarigan, 2018). Furthermore, The commitment of top management (OP) is essential for the assimilation of big data, the enhancement of organizational capabilities, and overall success, the findings show that via the mediation of top management commitment, the adoption of big data predictive analytics (BDPA) is positively connected with connections and information sharing (Gunasekaran et al., 2017).

In the workplace, commitment fosters creativity and innovation because it is a gauge of one's seriousness and attention to the success of the firm (Marques et al., 2014). Enthusiasm fades, and creative endeavors are less likely to succeed in the absence of a strong commitment (Hakimian et al., 2016). Consequently, encouraging a strong sense of corporate commitment is essential to advancing innovation.

Previous studies demonstrate that an employee's sense of commitment to the company and sense of belonging are greatly shaped by their perceptions of organizational support (POS), which are shaped by their physical and psychological surroundings (Holliman, 2012; Riad et al., 2016). This suggests that companies should allocate sufficient resources to foster innovation since insufficient resources can result in lower levels of commitment (Daly and Dee, 2006; Serhat et al., 2017).

- H_5: Management commitment plays a role in moderating the relationship between knowledge sharing and innovation.

4. MODEL OF THE STUDY

A conceptual framework has been created to examine the connection between organizational innovation as a dependent variable. (Chen et al., 2021) and big data as the independent

variable (Ghasemaghaei and Calic, 2019) in Jordanian banks. Literature indicates a strong and clear correlation between organizational innovation and big data, bolstering the theory that big data fosters business innovation.

The impact of big data's three primary features, volume, diversity, and velocity, on the organization's innovation performance has been investigated. Research shows that big data diversity and velocity have a significant influence on a company's innovation performance. Still, data volume has no detectable effect (Ghasemaghaei and Calic, 2020). One measurable mediating variable is knowledge exchange. More than other factors, the speed at which data is processed and evaluated influences improving creative performance (Lin and Lee, 2005) and management commitment moderating variable (Oropesa-Vento et al., 2015).

5. GAP OF STUDY

Few studies have specifically examined how Big Data impacts organizational innovation, even though the literature now in publication recognizes the revolutionary potential of this technology in banking (Günther et al., 2017) the majority of studies concentrate on broad benefits like better operational performance and decision-making, but they usually overlook how these advances encourage or hinder innovation (Dougherty, 2017), A more comprehensive examination of the factors that mediate and alter the link between "big data" and "company innovation" is required due to the dearth of empirical evidence. In particular, establishing a thorough framework to clarify this relationship in the banking industry requires acknowledging information exchange as a mediator and managerial commitment as a moderating component.

6. METHODOLOGY

The relationship between management commitment, organizational innovation, knowledge sharing, and large amounts of data adoption is methodically investigated using a quantitative research approach, surveys and structured questionnaires are used to collect numerical data for statistical analysis, which enables a quantitative knowledge of these linkages within Jordan's banking industry (Lutfi et al., 2023).

The questionnaires were emailed to the middle and top management of Jordanian banks to achieve the study's objectives. In 2025, the survey was distributed from September to December; the data-collecting period is planned to take into account the availability and workloads of participants, using a flexible timeframe and a tiered method to efficiently manage hectic schedules (McCall, 2020).

The research staff periodically evaluates how many people responded and modifies the plan as necessary to ensure a representative sample and efficient data collection, to maintain participants' interest and resolve any problems, reminders and follow-up emails are often sent out.

6.1. Sampling Method and Collection Procedure
The sample's 395 members, who come from middle management as managers of department and top-level managers provide a diversified representation of the banking sector, because of this diversity, a thorough understanding of how various organizational levels and functions view and impact the variables under investigation is possible, a random sample technique is used to guarantee that all community members have the same opportunity for selection, which increases the findings' generalizability to a wider range of Jordan Bank management and staff, our methodology guarantees that the sample is typical of job activities and hierarchical levels, while also acquiring a variety of viewpoints on big data usage and organizational innovation.

6.2. Analysis of Data
The (AMOS) program will use the technique of structural equation modelling (SEM), for statistical investigation (SEM) and will look at the structural relationships between knowledge sharing, organizational innovation, big data adoption, and management commitment, the (CFA) will assess the measurement model's precision and reliability to ensure that the observed variables accurately reflect their underlying latent components.

The article provides a comprehensive and accurate statistical analysis of the connections within the banking industry in Jordan. This approach uses AMOS for both CFA and SEM, allowing for the simultaneous examination of numerous relationships and the study of complex causal structures. (CFA) was used to evaluate the assessment model's appropriateness and the convergence validity of the study variables (SEM). Assumptions will be closely adhered to to guarantee model appropriateness and result accuracy; elements having load factors of at least (0.50) were retained to support measurement scales. Furthermore, all the measuring scale items were statistically significant ($P < 0.01$).

The evaluation model as a whole had suitable fit scores of $\chi^2 = (1166.364)$, df $= (499)$, $\chi^2/df = (2.337)$, relative fit index (CFI) $= 0.936$, Tucker–Lewis index (TLI) $= (0.928)$, incremental fit index (IFI) $= (0.928)$, the normalized root mean square residual (SRMR) $= 0.068$, and a root mean square of estimation (RMSEA) $= (0.058)$.

The model-fit indices for the confirmatory factor analysis (CFA) model are described in (Table 2). About the designated cut-off values, these values, which include (CMIN/DF, CFI, TLI, SRMR, and RMSEA) indicate a suitable match. This implies that there is a satisfactory degree of fit between the model and the data.

In addition, reliability of the measuring scales' internal consistency and dependability for the eight constructs used in this study were assessed. Values of composite reliability (CR) and Cronbach's alpha were computed (Table 1). All Cronbach's alpha and CR values for all constructs are larger than (0.70) which is considered a good result in terms of the metrics reliability, validity and internal consistency.

The average variance extracted (AVE) of each measurement scale was calculated (Table 1), and it was above the recommended cut-off value for all scales (0.50). This outcome confirms convergent validity and demonstrates that measurement scales effectively reflect their own constructs.

Table 1: Measurement model results

First-order constructs	Second-order constructs	Items	Means	Standard deviation	Factor loadings	Cronbach's alpha values	CR	AVE
Volume						0.868	0.871	0.628
		VOL4	3.516	0.054	0.718			
		VOL3	3.575	0.052	0.787			
		VOL2	3.486	0.054	0.856			
		VOL1	3,425	0.050	0.803			
Velocity						0.795	0.808	0.521
		VEL4	3.737	0.044	0.519			
		VEL3	3.375	0.053	0.787			
		VEL2	3.491	0.048	0.849			
		VEL1	3.678	0.045	0.689			
Variety						0.909	0.910	0.717
		VAR4	3.587	0.045	0.841			
		VAR3	3.623	0.048	0.820			
		VAR2	3.572	0.048	0.884			
		VAR1	3.532	0.050	0.841			
Veracity						0.922	0.923	0.749
		VER1	3.678	0.045	0.858			
		VER2	3.719	0.043	0.867			
		VER3	3.711	0.042	0.893			
		VER4	3.689	0.043	0.843			
Big Data						0.849	0.876	0.641
		Vol	3.500	0.888	0.798			
		Vel	3.570	0.745	0.674			
		Var	3.578	0.846	0.905			
		Ver	3.699	0.774	0.809			
Knowledge Sharing						0.896	0.898	0.689
		KS1	3.99	0.774	0.768			
		KS2	3.95	0.701	0.863			
		KS3	3.95	0.746	0.876			
		KS4	4.06	0.770	0.810			
Management Commitment						0.841	0.851	0.538
		MCM1	3.76	0.772	0.765			
		MCM2	3.67	0.843	0.782			
		MCM3	3.74	0.833	0.851			
		MCM4	3.54	0.972	0.578			
		MCM5	3.82	0.780	0.659			
Organizational Innovation						0.953	0.953	0.695
		OI1	3.82	0.815	0.841			
		OI2	3.84	0.778	0.852			
		OI3	3.85	0.831	0.813			
		OI4	3.88	0.784	0.849			
		OI5	3.83	0.779	0.866			
		OI6	3.82	0.808	0.802			
		OI7	3.86	0.749	0.846			
		OI8	3.86	0.769	0.805			
		OI9	3.79	0.772	0.825			

Average variation removed (AVE), composite dependability (CR)

The last stage of the measurement model was tested following Fornell and Larcker's advice for testing discriminant validity. They had to prove discraminant valideiky that square root of the AVE values for each construct was higher than correlation with other constructs. As can be seen in Table 3, the results of Fornell and Larcker criterion indicate that the factors have sufficient discriminant validity.

The off-diagonal show the inter-construct correlations and along the diagonal are displayed the square root of the Average Variance Extracted (AVE) for each construct. The diagonals

Table 2: Model-fit indices

Model	CMIN/DF	CFI	TLI	SRMR	RMSEA
CFA model	2.337	0.936	0.928	0.068	0.058
Cut-off value	Between 1 and 3	>0.90	>0.90	<0.08	<0.08

CFI: Comparative fit index. TLI: Tucker–Lewis's index, SRMR: Standardized root mean square residual, RMSEA: Root mean square of approximation

for the construct correlation estimates, which are larger than inter-construct correlations, are (0.810) of Big Data, (0.843) of Knowledge Sharing, (0.725) of Management Commitment and (0.825) of Organizational Innovation. (AVE) (the square roots

of all the latent factor correlations are less than their construct reliabilities) consolidates the discriminant validity at an acceptable level for all constructs.

We also conducted an analysis using the heterotrait-monotrait ratio (HTMT) (Henseler et al., 2015), (HTMT) should be used to evaluate discriminant validity in variance-based structural equation modelling since it has tighter requirements than traditional methods, all of the (HTMT) values are substantially below the (0.855) threshold, according to the results (Table 3), indicating adequate discriminant validity between the components, the (HTMT) values between the builds, in particular, ranged from (0.443 to 0.646), suggesting that every structure is distinct.

6.3. Structural Model Assessment
To verify the hypotheses and investigate the correlations between the variables, the researchers used SEM with AMOS) (24) In the structural model evaluation, the findings are presented in (Table 4 and Figure 1).

The Table 4 shows significant direct impacts of big data on knowledge sharing ($\beta = 0.396$, $P = 0.001$), backing up (H_1). The findings showed that big data practices had a strong direct impact on organizational innovation, indicating that big data had a beneficial influence on the degree of knowledge sharing inside the business ($\beta = 0.209$, $P = 0.001$), supporting H_2). Furthermore, knowledge sharing was found to have a significant direct impact on organizational innovation ($\beta = 0.284$, $P = 0.001$), supporting (H_3), emphasizing the role of knowledge sharing as a crucial mechanism in enhancing organizational innovation.

6.4. Mediation Analysis
To investigate the function of knowledge sharing as a mediator in the connection between organizational innovation and big data practices, a mediation analysis was carried out, using (AMOS), the researchers implemented bootstrapping re-sampling processes (24), to do the study, (5000) bootstrapping samples with (95%) confidence intervals (CIs) were created. The significance of the indirect impact was evaluated using the lower limit (LB) and upper bound (UB) of the bias-corrected (Cis) data. Knowledge sharing partially mediated the intervening impact, according to the mediation study's findings, which showed a (95%) confidence level that it is not equal to zero if neither of the (CI's) bounds contains zero.

The Table 5 shows the effect of big data techniques on organizational innovation was found to be mediated by knowledge sharing, with the (LB) at (0.085) and the (UB) at (0.225). This shows that integrating knowledge-sharing is essential to communicating how big data approaches impact organizational innovation. The total impact of big data approaches on organizational innovation was determined by adding the direct and indirect impacts. The total impact of big data practices on organizational innovation was shown to be equal to the sum of the direct impacts (0.209) and the indirect effects (0.112) that are mediated by knowledge sharing (0.321).

6.5. Moderation Results
Table 6 illustrates the relationship between (SH) and (OI) based on (CMC). The route from (SH) to (OI) shows an estimate of (0.131), a t-value of (2.915), and a standard error (S.E.) of (0.004)

Table 3: Results of selective validity

Factors	Fornell and larcker				Heterotrait monotrait ratio HTMT			
	1	2	3	4	1	2	3	4
B D	**0.810**							
KS	0.467***	**0.843**			0.443			
MCM	0.544***	0.487***	**0.725**		0.556	0.501		
O I	0.576***	0.585***	0.633***	**0.825**	0.544	0.593	0.646	

The diagonal (bold) of the matrix displays the square root of the extracted average variance (AVE). The correlations between constructs are shown on the diagonal. At the (0.001) level, significance is shown by***

Table 4: Results of direct effects

Direct effect	Standardized coefficients	Standard errors	t-Values	P-values	Decision
H_1: Big data→knowledge sharing	0.396***	0.045	8.559	0.001	Supported
H_2: Big data→organizational innovation	0.209***	0.045	4.474	0.001	Supported
H_3: Knowledge→sharing and organizational innovation	0.284***	0.040	6.981	0.001	Supported

Table 5: Mediation results (results of indirect consequences)

Hypothesized path	Indirect effect	Lower bound	Upper bound	P-values	Results
H_4: Big Data→practices knowledge Sharing Organizational Innovation	0.112***	0.085	0.225	0.000	Supported
Total Big Bata→practices Organizational Innovation	0.321***	0.191	0.435	0.000	Partial mediation

Table 6: Moderation results

Direct effect	Standardized coefficients	Standard Errors	t-values	P-values	Decision
H_5: Knowledge sharing×management commitment organizational innovation	0.131**	0.020	2.915	0.004	Supported

when moderated by CMC. This highly significant link (P < 0.01) indicates that the relationship between (SH and CMC) significantly increases (OI), resulting in a moderate effect.

Organizational innovation was substantially correlated with the interaction term between management commitment and information sharing (β = 0.131), (P < 0.01). At various management commitment levels, we plotted the interaction impact. Figure 2 illustrates how there was a higher correlation between organizational innovation and information sharing when management commitment was high.

Management commitment's moderating role in the association between organizational innovation and knowledge sharing.

Figure 1: Structural model assessment
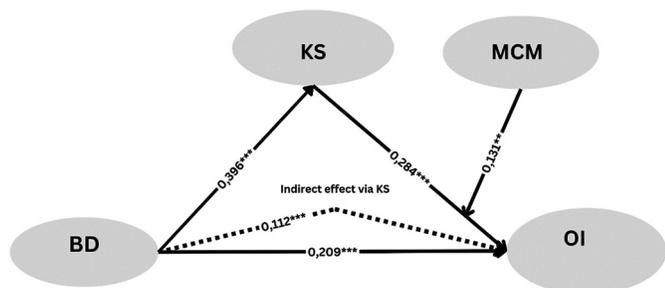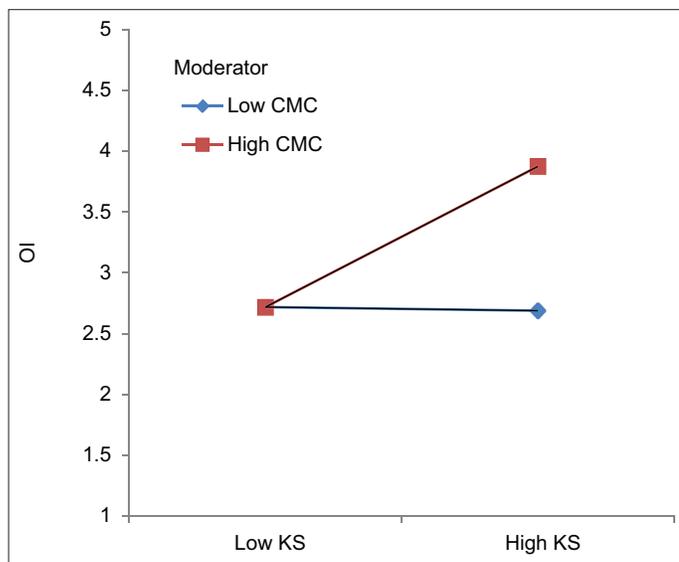

Figure 2: Model of study
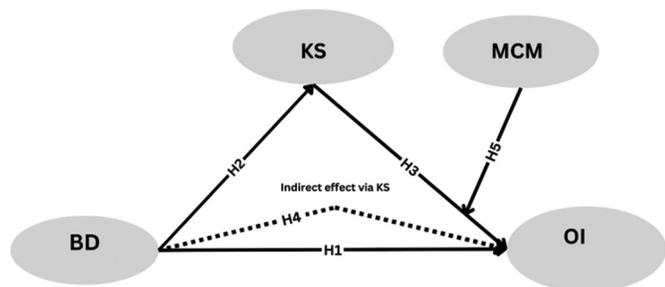
Figure 3: The moderating effect

Note that in Figure 3, KS stands for knowledge sharing, (OI) for organizational innovation, and (CMC) for management commitment (IDN).

7. RESULTS AND DISCUSSION

While convergent validity assesses the level of interaction between multiple measurements of the same construct and factor loadings demonstrate the magnitude and direction of the relationship between hidden constructs and measurable variables, reliability testing evaluates the stability and consistency of the measuring model. Conventional regression weights are used to determine the effect of a one average error change in the predictor variable on the dependent variable's value, the results of factor loadings, convergent validity analysis, and reliability testing will be presented and discussed in the following sections, offering insights into the measurement model's robustness and implications for the study's goals.

The results of this study are in line with those of other studies on the application of big data to organizational innovation in the banking sector (Ghasemaghaei and Calic, 2019; Wamba et al., 2017), Big Data's dimensions of volume, velocity, variety, and veracity have been found to influence innovation performance positively, our findings confirm these observations, particularly in Jordan banks, where data velocity and variety emerged as significant predictors of innovation outcomes, the impact of big data dimensions on innovation has not been discussed these findings highlight how crucial it is to handle vast amounts of varied data rapidly, a concept that is reflected in the work of (Van Rijmenam et al., 2019).

The current study showed that link between organizational innovation and big data practices was mediated by knowledge sharing (Nonaka and Takeuchi, 1995). Who emphasized that good knowledge sharing enables the organization to benefit from information-based insights and hence innovation. The mediation analysis demonstrated that knowledge sharing significantly enhances the impact of Big Data on innovation, reinforcing the importance of internal collaboration in data-rich environments (Chen et al., 2012).

Additionally, managerial dedication serves as a moderating factor to completely understand how Big Data affects innovation (Chadwick et al., 2015), top management support plays a critical role in fostering an organizational culture conducive to innovation, our findings demonstrate that management commitment enhances the relationship between innovation and information sharing, demonstrating that when leadership actively promotes knowledge integration, the total impact of Big Data innovation is enhanced, supporting the assertions about the strategic importance of allocating resources and offering administrative support for innovation initiatives (Sirmon et al., 2007).

Innovation, decision-making, and banking procedures have all been transformed by big data integration, big Data analytics are being used by banks more and more to get insights and enhance various areas of their business operations (Elhoseny et al., 2018), two barriers to effective Big Data integration are low entry barriers and the requirement for managerial experience (Kshetri, 2016).

8. SUMMARIZED FINDINGS

By validating statistically significant relationships between Big Data, knowledge sharing, management dedication, and organizational innovation, the validity study proves discriminant validity. Moreover, the Mahalanobis distance does not identify any outliers, and no construct is demonstrated to be unconnected to the (CFA) validity requirements.

It was shown that volume, velocity, and diversity had a substantial impact on the link between big data and organizational innovation, with knowledge sharing moderating the relationship and managerial commitment mediating it, by improving decision-making, reorganizing operations, and identifying new possibilities, big data analyses has completely transformed banking operations (Asurakkody and Kim, 2020), Big data also spurs innovation in the financial industry, resulting in change and bettering client experiences (Singh and El-Kassar, 2018).

Data-driven innovation fosters innovation in a variety of sectors by utilizing technological and analytical know-how together with lower data processing costs (Mosig et al., 2021), Innovation management software enhances data-driven innovation by facilitating access to several data sources and speeding up innovation processes (Afuah, 2003). Consequently, data-driven decision-making enables adaptable innovation strategies and prompt responses to industry changes and obstacles (Bresciani et al., 2021).

According to Tunc-Abubakar et al. (2023), Big data analytics and software for innovation management are crucial for promoting data-driven innovation, giving companies comprehensive insights, assisting in well-informed decision-making, and cultivating agile innovation processes.

Big data is increasingly being used to promote knowledge sharing, accelerate innovation, and create an organizational culture of learning, although organizational creativity is greatly impacted by volume, velocity, and diversity, knowledge exchange and management commitment serve as moderating and mediating factors between big data and innovation, respectively, with an emphasis on the advantages of velocity and variety, the report emphasizes how crucial big data is to improving organizational processes and performance. It has been demonstrated that performance innovation and data-driven decision-making are supported by big data analytics' rapidity of data collection and comprehension.

- There is a statistically significant correlation between organizational innovation and the Big Data characteristics of volume, vKelocity, diversity, and veracity, especially when knowledge exchange is included as a mediator
- Knowledge sharing acts as a mediator in the interaction between Big Data and innovation, highlighting the importance of internal collaboration in applying data insights
- Management commitment increases the impact of knowledge sharing on innovation.

9. CONCLUSION

To clear things up, big data analytics is a major driver of the technological change that Jordanian banks are going through, banks may improve performance, spot patterns and make well-informed decisions by utilizing intelligent models and analyzing huge information banks may improve internal procedures, offer novel goods, services and create unique customer experiences with.

Even though big data has many advantages, banks find it difficult to use it effectively to spur organizational innovation, to remain competitive in the dynamic market, banks need to understand the complex interplay between organizational innovation and big data usage leaders and managers must effectively allocate resources and foster an innovative culture within banks to speed up and improve the efficacy of big data analysis in the end, banks must commit to proactive resource allocation and management to fully utilize big data analytics and spur innovation in the financial services sector.

This study demonstrates how important big data is for fostering organizational innovation in the banking industry in Jordan, highlighting the importance of data velocity and variety as key drivers of innovation. Knowledge sharing acts as an important mediator that helps to translate Big Data applications into actionable innovation. In addition, management commitment moderates the relationship between knowledge sharing and innovation, highlighting the role of leadership in creating a culture of data-driven innovation.

10. RECOMMENDATIONS

Training and development to move beyond the reluctance of new technology adoption and create a culture of learning where personnel leverage big data insights with innovative client offerings, ensure oversight is in place to have the skills necessary to embed big data analytics into decision-making: Managers and leaders should provide training and development around using big data insights as an input in creating challenging options.

Fast Reaction Time in the Face of Change Big data insights afford an adjustable reaction to local and regional variables, helping banks managing against a backdrop with ever-shifting sands. Banks must act quickly to the changing requirements of their customers and the world economy.

Big data skills analytics of Big Data in the Banking Industry There is a need for a detailed analysis of how various big data strategies, tools and approaches impact on banking innovation. Big data initiatives should be scheduled and guided by Organizational bosses to align with strategic objectives and facilitate assimilation of insights within the decision-making process and resources allocation. In order to promote the integration of big data analytics, Cultural Leadership Management should reserve budget for training and knowledge enlarging platforms.

As we know, culture leads to creativity.

Sharing, knowing and using analytic technologies banks must also share big data analytics technologies and know how to use them if they are to maintain operational performance. Through various analytic software solutions, banks improve organizational innovation ultimately allowing for better business decisions and hence enhancing organization's success.

- Invest in knowledge sharing platforms: Companies should invest in the systems that improve cross-departmental knowledge sharing, particularly in data-based industries
- Management training: Leaders need to be educated on the strategic value of big data and how their commitment could amplify the outcomes from innovation
- Pay attention to data velocity and variety: Financial institutions will need technology that facilitates faster, simpler analysis of data types from many varied sources if they want to be truly competitive and innovative.

11. FUTURE IMPLICATIONS

The role of big data analysis in Jordan banks has been underscored Based on the results of this study, it has been concluded that big data analysis is important for organizational performance and innovation as well as how it will aid banks to be ahead competently there was no further detail given to establish advantages associated with big data or strain on financial business sector though. Additionally, the big data in banks (in general) and in Jordanian banks, in particular must be studied more extensively to develop these institutions performance and creativity.

The developing roles of (AI) in strengthening the connection between organizational innovation and big data should be the subject of future studies. Furthermore, a more thorough examination of how management commitment affects innovation sustainability over the long run using data-driven tactics is necessary, especially in sectors like banking that undergo fast change Given that certain businesses are highly interconnected and productive, (AI) is crucial for big businesses, (AI) is being utilized more and more in business design to get insights and enhance the manufacturing process in particular, which helps businesses reach their objectives. Large data sets are also analyzed by (AI) to create prediction models that can be used to swiftly and accurately report on the smart firm and concentrate on innovation. Analysis driven by industrial AI may also give the business insights into its performance in real-time, allowing them to spot areas for improvement and move swiftly to address them.

Hence, we propose that the academia focus on AI because it enhances innovation for companies; however providing them with a big competitive advantage. To generalize the results, we also recommend replicating this study in different regions and focusing on developing countries especially those located in the Middle East such as Jordan, Syria and so forth that tend to move forward efficiently in all aspects of life.

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